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A multi-agent based scheduling algorithm for adaptive electric vehicles charging

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HIGHLIGHTS

- A decentralised EV charging control model was developed.
- EV were separated in "Responsive" and "Unresponsive" EV to control signals.
- Generation and demand forecasts were considered in the charging control model.
- The adaptive behaviour of Responsive EV agents was experimentally demonstrated.

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ABSTRACT

This paper presents a decentralized scheduling algorithm for electric vehicles charging. The charging control model follows the architecture of a Multi-Agent System (MAS). The MAS consists of an Electric Vehicle (EV)/Distributed Generation (DG) aggregator agent and "Responsive" or "Unresponsive" EV agents. The EV/DG aggregator agent is responsible to maximize the aggregator's profit by designing the appropriate virtual pricing policy according to accurate power demand and generation forecasts. "Responsive" EV agents are the ones that respond rationally to the virtual pricing signals, whereas "Unresponsive" EV agents define their charging schedule regardless the virtual cost. The performance of the control model is experimentally demonstrated through different case studies at the micro-grid laboratory of the National Technical University of Athens (NTUA) using Real Time Digital Simulator. The results highlighted the adaptive behaviour of "Responsive" EV agents and proved their ability to charge preferentially from renewable energy sources.

1. Introduction

The integration of electric vehicles is considered as a promising alternative to reduce transportation related emissions and improve energy consumption efficiency. Recent studies [1–3] reveal that a fuel-driven vehicle can produce less greenhouse gas emissions (GHG) than an EV if the recharging energy is entirely produced by coal-fired power plants. Therefore, charging EV from renewable energy (e.g. solar, wind) significantly contributes to achieve real environmental benefits.

However, it is difficult to effectively utilise this intermittent and dispersed generation capability due to its direct dependency on local weather factors. High penetration levels of renewable energy resources and other low carbon generation technologies are affecting the generation mixture of each country. At those high uptakes, the distributed generators will cause voltage rises during times of low demand at the low voltage (LV) feeders [4–12].

In addition, changes in the electricity demand will occur as a result of EV uptake. Due to the temporal and spatial variability of EV charging energy patterns, the load demand at the national level is expected to increase. According to [13–20] the impacts of EV charging in distribution network will create higher power peaks, overload power transformers, cause voltage drops and line overloading.

Demand side management is seen as an effective solution to address these challenges in the existing distribution networks. Electric vehicles offer opportunities for effective demand side management, utilising their flexibility with regards to the time of charging. Therefore, EV charging management is a potential candidate solution to shift charging demand based on the renewable energy production or to shift charging to off peak hours, decreasing voltage fluctuation and transformer loading.

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Due to the EV impacts on distribution networks, EV charging control models have attracted substantial research attention [21]. In literature, there are two main types of EV charging control models: the centralized and the decentralized. In a centralised control strategy, a central control unit is responsible to manage the EV charging demand, controlling directly the charging process of each EV. Such examples of control strategies can be found in [22–44]. Although this control strategy offers a simple way to manage the EV charging requests, it is not appropriate for large numbers of EVs as it requires high computational power and an advanced communicational infrastructure to avoid delays and enable real time operation. Concerns have also been expressed regarding the data privacy of the EV drivers, as their charging habits and information would be collected in one place, increasing the risk of being exposed to malicious cyber-attacks.

Decentralised control approaches, where the intelligence is distributed among the components of the system, are seen as a potential solution to overcome these problems. Papers [45–51] present decentralized control models for coordinating the EV charging. In these papers, the decision making processes are mainly done by the EVs which only require knowledge of the local condition of the system. Therefore, the complexity of such control approaches is usually low and the computational and communicational cost is reduced compared to the centralised approaches. Decentralised price-based EV charging control strategies have also been investigated in [52–56] for the control of Distributed Energy Sources (DER)/DG, assuming that an appropriate pricing scheme could trigger certain responses from the participants. Paper [55] presents a market clearing model which does not require any centralized knowledge of participants' properties. The model is extended in [52], however its feasibility is not ensured with respect to nodal power balance constraints when the participant's coordination problem is not strictly convex. In order to address this issue, the authors of [56] are using the primal average technique on all the past iterations in order to show an asymptotic convergence to a feasible and optimal solution. However, this approach is not always feasible due to the huge computational and communicational costs it creates. The infeasibility problems of [52] are solved in [54], where the price responses of non-strictly convex DERs are considered fixed. However this approach creates significant new demand peaks, as the price responses are concentrated at the lowest-priced periods of the coordination horizon. To overcome this problem, a non-linear pricing scheme is adopted in [53]. In these control approaches, the synchronisation of the participants is critical. The existing approaches require simultaneous exchange of information among all participants which might lead to response delays or even lost information. To the best of the authors' knowledge this problem is not addressed in the literature when considering a decentralised EV charging management scheme.

All the above references suffer from the assumption that every available DG/DER is controllable and responds logically to a pricing scheme, without considering uncertainties related to the EV driver preferences. EV charging coordination is highly affected by the EV driver behaviour, as the driver decides when and how to charge its vehicle. Dealing with the uncertainties related to the EV charging patterns is important for all charging control models. In [23,27,28,31], forecasting actions are included in the presented centralised charging control models. Statistical models and Markov-processes are used to deal with the uncertainties related to the EV travel patterns [23] and renewable generation output [31]. In the majority of these papers, it is mentioned that the performance of the control model is depended on the accuracy of the predictions. According to the best of the authors' knowledge, there are no decentralised charging control models utilising forecasting procedures to deal with the uncertainties regarding EV participation in the control scheme.

In this paper a decentralized scheduling algorithm for EV charging is presented. The charging control model follows the architecture of a Multi-Agent System (MAS). Each entity was modelled as an autonomous agent, which interacts with other agents and tries to achieve its own goals. The MAS consists of an EV/DG aggregator agent and "Responsive" or "Unresponsive" EV agents. The EV/DG aggregator agent is responsible to maximize his profit by designing the appropriate virtual pricing policy according to accurate power demand and generation forecasts. Responsive EV agents are the ones that respond rationally to the virtual pricing signals, whereas Unresponsive EV agents define their charging schedule regardless the virtual cost. Responsive EV agents are adjusting their charging schedules according to the charging demand from "Unresponsive EV agents", indicating their adaptive behaviour. A novel algorithm was developed for the distributed management of EV charging. Although the EV agents are selfishly trying to minimize their virtual cost, this results in a valley-filling effect on the total demand curve. This is achieved through the dynamic pricing mechanism of an EV/DG aggregator. The virtual pricing scheme is used only for the coordination purposes of the EV/DG aggregator and does not reflect the actual network charges or market prices. It is assumed that all EV owners that participated in the charging management scheme will be benefited from a lower electricity rate. The actual charging cost of each EV owner is post calculated but this is out of the scope of this paper.

The main technical contributions of this paper are as follows:

(i) The proposed control model considers a realistic scenario for the future EV fleet by classifying the EV agents into Responsive and Unresponsive to the control strategy.
(ii) A forecasting model is integrated to the decentralised charging control model in order to reduce the uncertainties associated with the participation of EVs to the management scheme.
(iii) The synchronisation of the EV charging coordination is achieved by a novel approach involving sequential updates of the charging control signals. By modifying the virtual control price signals after each charging request sequentially, the Responsive EV agents adapt their charging demand to the demand from the Unresponsive EV agents.
(iv) The performance of the control model was experimentally demonstrated at the Electric Energy Systems Laboratory hosted at the National Technical University of Athens (NTUA). Three factors were investigated: (a) the location of the EV/DG aggregator, (b) the importance of forecasting the demand from Unresponsive EV agents and (c) the charging behaviour of Responsive EV agents when renewables generation is available. The results showed the adaptive behaviour of Responsive EV agents and proved their ability to charge preferentially from Renewables.

The rest of the paper is organized as follows. In Section 2 the EV Management Framework is illustrated. The experimental demonstration of the charging control model is described in Section 3. Conclusions are drawn in Section 4.

2. EV management framework

2.1. Architecture

The EV management scheme follows a two-layer decentralized structure based on the UK generic distribution network [57]. The bottom layer includes the EV agents at the LV customer level,